Supplement Materials

Detailed review of BDA applications based on each SC function

1. Procurement

[Table A1: Summary of BDA in procurement]

BDA in procurement lies on supply management, spend analysis and risk prediction. Research on supplier selection and relationship development inherits conventional process where a number of selection criteria are set up in first place. The role of BDA is to enable these criteria to be able to expand to a considerable multifaceted scale, i.e. multi-dimensions and multi-layers of multi-criteria, which reflects the comprehensiveness of supply management (Choi et al., 2016; Jain et al., 2012; Mori et al., 2012). The supplier selection often accompanies with effort of reducing cost through allocating order quantity between key suppliers (Kuo et al., 2015), improving purchasing process (Melvin Tan and Wee-leong, 2015), predicting uncertainties (Ahiaga-dagbui and Smith, 2014) and estimating pricing risk (Huang and Hanfield, 2015). Moreover, BDA also expedites risk management through established warning system of abnormal events (Ling Ho and Wen Shih, 2014), detecting suppliers cartel (Ralha and Silva, 2012) and corruption (Miroslav et al., 2014).

It is noted that developing a knowledge base (KB) for decision-making and risk identification is a common practice. The KB serves as a reference and benchmarking to various supplier selection criteria development and risk detection alteration. Nevertheless, research on developing a comprehensive KB itself is rather scarce.

In terms of techniques, BDA in supplier selection has been using 'static' historic data to help make decision. There seems to lack of research of using real-time data that can enable dynamic contracting and relationship between customer and supplier in line with the changing business environment.

2. Manufacturing

[Table A2: Summary of BDA in manufacturing]

BDA in manufacturing is to streamline manufacturing process by identifying core determinants that influencing SC performance as a whole, and then taking actions to continuously improve them. This has been studied in four aspects: product R&D, production planning and control, quality management, diagnosis and maintenance, as presented in Table A2.

Product R&D heavily relies on extracting various forms of customer feedback (Kwon and Kim, 2011; Lei and Moon, 2015). Through BDA, the result of these feedback analyses can lead to enhanced innovation capability (Tan et al., 2015) and monitoring on-going product development performance (Do, 2014). It also exploits the new revenue generation streams and opens opportunities for cost reduction (Opresnik and Taisch, 2015). Yet, the production quality can be seen as one of key performance indicators (KPIs). However, BDA application on this area is only partially explored in literature, and mostly discussed along with other activities in manufacturing process such as production planning and control, resources allocation and process monitoring (Zhang et al., 2015; Krumeich et al., 2015). Studies that focus particularly on BDA-driven quality control are very few (Zhang et al., 2015).

Applying BDA in diagnosing machine fault and planning for maintenance is another area that has been gained rising attentions of academic. It is expected that the system would be able to automatically detect the failure and be capable of taking action without human intervention (Zhang et al., 2015; Kumar et al., 2016; Wang et al., 2015; Shu et al., 2015). The fault refers not only machines but also workers' abnormal behaviours (Guo et al., 2016). It is interesting to note that this is one of few areas for which the BDA techniques are developed to accommodate distributed agents such as cloud-based platform, machines, conveyers, products, to name a few.

Finally, BDA in production planning and control dominates over the above three aspects in manufacturing management. In order to meet customer demand, production planning and control must be aligned, which requires accurate forecasting in terms of production order arrivals (Zhong et al., 2015) and production cycle time (Wang and Zhang, 2016). By doing this, RFID-enabled production scheduling can allocate resources effectively (Wang and Zhang, 2016; Zhong et al., 2015) and release the shop floor planning (Zhong et al., 2015; Wang and Zhang, 2016; Lan, et al., 2015). In many cases, the planning and control executes through RIFD/sensors-enabled real-time intelligent cloud manufacturing system (Zhong et al., 2015; Zhong et al., 2015; Zhong et al., 2015; Helo and Hao, 2017). The applied BDA techniques are rather diversity, for instance, event-based processing prediction (Krumeich et al., 2015), heuristic based optimisation (Zhong et al., 2015), or bespoke algorithm developed for a specific platform (Zhong et al., 2015)

3. Logistics and Transportation

[Table A3: Summary of literature on BDA in Logistics/Transportation]

Overall, the study of BDA in logistics/transportation area is quite extensive but rather unbalanced. As can be seen in Table A3, transportation management prevails among this area with more than half of research (15 out of 24 papers, 62.5%). Meanwhile, BDA-driven logistics planning is still under-investigated (7 papers, 29.2 %) and in-transit inventory management is seldom discussed.

As regarding to transportation management, the ultimate objective of BDA adoption is to develop Intelligent Transportation System (ITS) that allows real-time traffic operation control and proactive safety management. Traffic operation efficiency can be improved either by accurately and timely prediction of short-term traffic flow demand (Xia et al., 2015; Li, Su, et al., 2015) or by using smart routing to avoid traffic congestion (Zhang et al., 2016; Fabian et al., 2016) whilst safety is mainly studied through crash analysis (Yu and Abdel-Aty, 2014; St-Aubin et al., 2015; Zangenehpour et al., 2015). It should be noted that Shi and Abdel-Aty (2015) is the only paper found in the examined literature that highlights the importance of jointly controlling and improving both traffic operations and safety simultaneously. In addition, most of studies above develop BDA-based models in static settings, whereas real-time decision-making support such as dynamic routing optimization or proactive traffic monitoring are only conceptually discussed in platfrom-based papers (Dobre and Xhafa, 2014; Wang et al., 2015; Toole et al., 2015; Hsu, Yang, et al., 2015, Sivamani et al., 2014).

Regarding to logistics planning, BDA can facilitate a range of strategic and operational decisions. For example, at strategic level, Tu et al. (2015) and Shan and Zhu (2015) analyzed large-scale GPS data to optimize facility location. Mehmood et al. (2017) used a Markov model to demonstrate how big data could be leveraged for optimise transport load sharing in smart cities to improve transport efficiency and reduce externalities. For operational capacity planning, Lee (2016) and Liu and Wang (2016) optimize order allocation and shipping assignment by extracting a sheer amount of customer location and consumption data for higher prediction accuracy of customer demand. Li et al. (2014) take advantage of massive historical data from detectors to accurately predict failures in rail operation, thereby optimizing maintenance scheduling. Noteworthy, the adoption of BDA approach in more holistic SC network design models that optimize both strategic and operational decisions simultaneously is still extremely limited (Zhao et al., 2016; Prasad et al., 2016).

To logistic and transportation planners, the major concern on inventory management is to define appropriate logistics plans in order to maintain the quality and safety of the product during in-transit process. From this viewpoint, BDA provides unprecedented opportunities for tracking, assessing and monitoring the product conditions in accordance with in-transit context, including temperature, vibration, moisture, light exposure, and humidity level. However, such decision support system (DSS) allowing in-transit inventory management is currently far less studied in literature, compared to other BDA-enabled logistics applications (Ting et al., 2014; Delen et al., 2011).

4. Warehousing

[Table A4: Summary of literature on BDA in warehousing]

Efficiently handling and storing products and materials are the vital roles of warehousing. BDA applications in this supply chain function have focused particularly on material handling and layout zoning to maximizes space utilization, minimize distance travelled to fulfil orders and consequently minimize storage and material handling costs and risk of hazard events. A wide range of factors affect the way warehouses are managed, such as size and layout of storage and material handling systems, order picking policies, product features, order frequencies, demand trends, turnover rate, etc. (Chan and Chan, 2011). Data mining-based storage assignment methods have been used to process data on orders, products and customer constantly and automatically saved in warehouse management systems (WMS) and Enterprise Resource Planning (ERP) systems (Chuang et al., 2014; Chiang et al., 2011; Chiang et al., 2014; Li et al., 2016). In addition, mining of data collected through RFID enables the effective shelf space allocation and product positioning in retail shops considering customer purchase and browsing behaviours (Tsai and Huang, 2015).

While the use of BDA in storage assignment is quite extensively studies, its adoption in order pick is far less behind. Indeed, studies often discussed the advantages of BDA on order picking efficiency as a by-product of BDA-based optimal storage assignment (Chuang et al., 2014), while the study of how BDA can optimise order picking processes, such as order batching, routing, and sorting, is still scare (Ballestín et al., 2013; Alyahya et al., 2016).

A basic element of customer service is inventory availability. Inventory control has significant impacts across the whole SC process and directly dictates warehouse operations. Its primary task is to determine the right stock level that balances the inventory holding cost and the cost of lost sales. From this viewpoint, BDA has emerged as a key tool to support inventory managers. Indeed, the adoption of BDA stimulates collaborative planning, forecasting and replenishment (CPFR) implementation, which enables the real-time access, amalgamation and extraction of massive data from heterogeneous inventory points including procurement, production, distribution, and point of sale in order to produce fast, accurate, and reliable inventory replenishment predictions (Prajogo and Olhager, 2012). Previous research has explored the combination of traditional inventory planning and control methods with other data sources, such as clickstream data (Huang and Van Mieghem, 2014), manufacturing and customer behaviour data (Hsu et al. 2015) and counterpart stores and franchisers data (Stefanovic, 2015; Lee et al., 2015). The latter two works demonstrated the power of information sharing to improve inventory replenishment. By consolidating retail store data (Stefanovic 2015) and developing and exploring a cloud-based environment for real-time data sharing between franchisers (Lee et al. 2015), responsive replenishment systems were created.

Although it is well established that supply chain dynamics such as bullwhip effect, backlash effect and ripple effect are driven by different inventory control policies, the only study to cover this subject was Hofmann (2015). In a theoretical analysis, he explored an inventory control model to determine which characteristics of Big Data (volume, variety and velocity) are most likely to mitigate the bullwhip effect.

5. Demand management

[Table A5: Summary of literature on BDA in demand management]

BDA have been applied in demand management for demand forecasting, sensing and shaping. Demand forecasting normally requires predictive analytics using time-series approaches, auto-regressive methods and associative forecasts (Wang et al., 2016)

The contribution of BDA in demand foresting has been on the association of time-series methods with other product- and market-related attributes. For instance, Ma et al. (2014) developed a Demand Trend Mining algorithm, which combines time series forecasting with product design attributes. Another example is the correlation found between time-series data on online search traffic information and oil price, consumer price index and product market share (Jun et al., 2014). Hence, search traffic can be used as an additional associative forecasting resource for certain products. In Berengueres and Efimov's (2014) work, regression methods were also used to integrate data in loyalty card to improve demand predictions.

Demand sensing in combination with BDA techniques has enabled companies to incorporate detailed short-term and real-time demand data into their forecasts. For instance, some studies have demonstrated how online reviews (Chong et al., 2016; Fang and Zhan, 2015; Li et al., 2016) and social media data (He et al., 2015) can be used to determine the predictors of product sales in both e-commerce and retail business. By using sentiment analysis and text clustering, these studies were able to translate unstructured comments to describe and predict customer behaviour. Another research stream has made efforts to analyse the readership and helpfulness of online comments for both vendors and consumers (Salehan and Kim, 2015). Search traffic information, loyalty cards and mobile network data have also proven to be useful in sensing demand through customer segmentation (Berengueres and Efimov, 2014, Wang et at., 2014; Jun et al., 2014). Detecting customer behaviour and predicting market volatility have underscored the opportunity to sense and react in near real-time to changes in the demand.

After forecasting and sensing demand, BDA can be applied to shape demand, such as by price management (Schmidt et al., 2015), marketing and advertisement (Chong et al., 2016), managing online reviews (Salehan and Kim, 2015), long-term marketing campaigns and planning policies, improving branding (Marine-Roig and Clave, 2015), improving customer experience (He et al., 2015) and product life cycle management (Ma et al., 2014). Although demand shaping is one of the operational supply chain management strategies for effective capacity planning, previous research has taken more the marketing intelligence perspective.

6. General SCM

[Table A6: Summary of literature on BDA in "General SCM" papers]

We found 6 papers that, instead of focusing on a single SC function, examined the application of BDA considering SCs as multi-level interconnected networks (Table A6). These papers have addressed different SC issues concerning resilience (Sheffi 2005; Papadopoulos et al., 2016), sustainability (Papadopoulos et al., 2016; Wu et al., 2016), risk management (Ong et al., 2014) and agility (Giannakis and Louis, 2016). However, most of them propose theoretical framework or use real-world cases to illustrate how companies are currently using sensors, social media, and event monitoring web-services to improve risk detection, response and traceability. Two notable exceptions are Wu et al. (2016) and Giannakis and Louis (2016). The former used BDA to transform social media data into manageable information so that companies can quickly respond to customer needs. Likewise, Giannakis and Louis (2016) created a multi-agent based SCM system that incorporates autonomous corrective control actions to answer to different SC partners' requirements. Finally, by using a completely different angle from all the mentioned papers above, Zou et al. (2016) provides technical solutions for improving real-time data processing and accuracy in interconnected SC network nodes.

Table A1: Summary of literature on BDA in procurement

Article	Research Type	Supplier Selection	Sourcing cost improvement	Sourcing risk management	Level of analytics	BDA model type	BDA techniques
Choi et al. (2016)	Model	*			Prescriptive	Simulation	Fuzzy cognitive mapping
Mori et al. (2012)	Model	*			Predictive	Classification	Support vector machine
Jain et al. (2012)	Model	*			Descriptive	Association	Fuzzy association rule mining
Huang and Hanfield (2015)	Model	*	*	*	Descriptive	N/A	SC maturity rating model
Kuo et al. (2015)	Model	*	*		Prescriptive	Optimisation	Association rule mining, artificial immune network, Particle swarm optimization
Melvin Tan and Wee-leong (2015)	Model		*		Descriptive	Clustering	Text mining, K-mean clustering
Ahiaga-dagbui et al. (2014)	Model		*		Predictive	Forecasting	Artificial neural network
Ho and Shih (2014)	Platform			*	Predictive	Classification	Association rule mining, decision tree
Ralha and Silva (2012)	Model & Platform			*	Predictive	Association	EM Clustering, association rule mining
Miroslav et al. (2014)	Model & Platform			*	Predictive	Semantic analysis	Meta-Model

Table A2: Summary of literature on BDA in manufacturing

Article	Research types	Product research & development (R&D)	Production planning & control	Quality management	Maintenance & diagnosis	Level of analytics	BDA model type	BDA techniques
Zhang et al. (2016)	Platform	*	*	*	*	Prescriptive	Mixed/others	Mixed
Tan et al. (2015)	Model	*				Prescriptive	Optimisation	Deduction graph
Lei and Moon (2015)	Model & Platform	*				Prescriptive	Simulation	K-means clustering, AdaBoost classification, Sensitivity analysis
Do (2014)	Platform	*				Descriptive	Visualisation	OLAP
Bae and Kim (2011)	Model	*				Descriptive	Association	Association rule mining, decision tree
Opresnik and Taisch (2015)	Theory	*				Descriptive	N/A	N/A
Zhong et al (2015)	Model		*			Prescriptive	Optimisation	Heuristic approach
Wang and Zhang (2016)	Model		*			Predictive	Classification	Mixed
Li et al. (2016)	Model		*			Prescriptive	Optimisation	Heuristic approach
Chien et al. (2014)	Model		*			Predictive	Classification	K-mean clustering, decision tree
Helo and Hao (2017)	Theory		*			Prescriptive	Optimisation	Mixed
Krumeich et al. (2015)	Theory		*	*		Prescriptive	Mixed/others	Mixed
Zhang et al. (2015)	Model			*		Prescriptive	Simulation	Spatial-temporal visualisation
Wang et al. (2016)	Model			*	*	Prescriptive	Simulation	Agent based simulation
Kumar et al. (2016)	Model				*	Predictive	Classification	Support vector machine
Wang et al. (2015)	Theory				*	Predictive	Classification	Feature selection, support vector machine
Guo et al. (2016)	Platform				*	Predictive	Semantic analysis	Text mining
Shu et al. (2016)	Theory		*		*	Predictive	Classification	Entropy method, artificial immune network
Zhang et al., (2015)	Model & Platform		*			Prescriptive	Optimisation	Spatial-temporal visualisation, dynamical optimisation
Dai et al. (2012)	Platform		*			Prescriptive	Mixed/others	Mixed
Zhong et al. (2015)	Model		*			Prescriptive	Mixed/others	Mixed
Zhong et al. (2015)	Platform		*			Descriptive	Visualisation	Spatial-temporal visualisation
Zhong et al. (2015)	Model & Platform		*			Predictive	Regression	Curve fitting

Table A3: Summary of literature on BDA in Logistics/Transportation

Article	Research type	Intelligent transportation system	Logistics planning	In-transit inventory management	Level of analytics	BDA model type	BDA techniques
St-Aubin et al. (2015)	Model	*			Descriptive	Clustering	K-means clusters, heat map
Shi and Abdel-aty (2015)	Model	*			Predictive	Regression	Random forest, Bayesian logistic regression
Yu and Abdel-aty (2014)	Model	*			Predictive	Classification	Support vector machine, logistic regression
Zangenehpour et al. (2015)	Model	*			Predictive	Classification	Support vector machine
Wang et al. (2015)	Platform	*			Prescriptive	Optimisation	Fuzzy logic, generic algorithm (GA)
Xia et al. (2015)	Model	*			Predictive	Forecasting	Distributed K-Nearest neighbour
Li et al. (2015)	Model	*			Predictive	Forecasting	Granger causality, Lasso regression
Cui et al. (2015)	Model	*			Descriptive	Association	Descriptive statistics
Walker and Strathie (2015)	Model	*			Descriptive	Clustering	Mixed
Dobre and Xhafa (2014)	Platform	*			Prescriptive	Mixed/others	Mixed
Toole et al. (2015)	Platform	*			Prescriptive	Optimisation	Heuristic approach
Fabian et al. (2016)	Model	*			Prescriptive	Optimisation	Heuristic approach
Zhang et al. (2016)	Model	*			Prescriptive	Optimisation	Spatial-temporal visualisation; heuristic approach
Hsu et al. (2015)	Platform	*			Prescriptive	Mixed/others	Mixed
Sivamani et al. (2014)	Platform	*			Prescriptive	Optimisation	OWL (Ontology Web Language)
Mehmood et al. (2017)	Model		*		Prescriptive	Optimisation	Markovian approach
Lee (2016)	Model		*		Prescriptive	Optimisation	Association rule mining, if-then prediction, generic algorithm (GA)
Yan-Qiu and Hao (2016)	Model		*		Prescriptive	Optimisation	Association rule mining, time-series forecasting, simulation
Zhao et al. (2016)	Model		*		Prescriptive	Optimisation	Mixed
Prasad et al. (2016)	Model		*		Descriptive	Association	Resource Dependence Theory
Shan and Zhu (2015)	Model		*		Prescriptive	Optimisation	Spatial-temporal visualisation, heuristic approach
Tu et al. (2015)	Model		*		Prescriptive	Optimisation	Spatial-temporal visualisation, generic algorithm (GA)
Li et al. (2014)	Model		*		Predictive	Classification	Support vector machine
Ting et al. (2014)	Model			*	Prescriptive	Simulation	Association rule mining, Dempster's Rule of combination
Delen et al. (2011)	Platform			*	Prescriptive	Mixed/others	Mixed

Table A4: BDA in warehousing

Article	Research type	Storage assignment	Order picking	Inventory control	Level of analytics	BDA model type	BDA techniques
Chuang et al. (2014)	Model	*	*		Descriptive	Association	Descriptive statistics, association rule mining
Chiang et al. (2011)	Model	*			Descriptive	Association	Association rule mining
Chiang et al. (2014)	Model	*			Descriptive	Association	Association rule mining
Tsai and Huang (2015)	Model	*			Prescriptive	Optimisation	Association rule mining, sequential pattern mining, combinatorial optimisation
Li, Moghaddam et al. (2016)	Model	*			Prescriptive	Optimisation	Association rule mining, generic algorithm (GA)
Ballestín et al. (2013)	Model		*		Prescriptive	Simulation	Heuristic approach
Alyahya et al. (2016)	Model & Platform		*		Prescriptive	Optimisation	Logistic regression
Huang and Van Mieghem (2014)	Model			*	Predictive	Regression	K-means clustering, decision tree, neural networks
Stefanovic (2015)	Model & Platform			*	Predictive	Forecasting	Fuzzy logic
Lee et al. (2015)	Model & Platform			*	Prescriptive	Optimisation	Neural networks
Hsu, Lin, et al. (2015)	Model			*	Predictive	Forecasting	Z-transforms and system dynamics simulation
Hofmann (2015)	Model			*	Prescriptive	Simulation	Spatial-temporal visualisation, heuristic approach

Table A5: Summary of literature on BDA in demand management

Article	Research type	Demand forecasting	Demand sensing	Demand shaping	Level of analytics	BDA model type	BDA techniques
Berengueres and Efimov (2014)	Model	*	*		Predictive	Forecasting	Decision tree, logistic regression
Jun et al. (2014)	Model	*			Predictive	Forecasting	Time-series forecasting
Ma et al. (2014)	Model	*			Predictive	Semantic analysis	Sentiment analysis, neural network
Li, Ch'ng et al. (2016)	Model		*		Descriptive	Association	Hierarchical multiple regression analysis
Wang, Tu et al. (2014)	Model		*		Predictive	Forecasting	Decision tree, automatic time-series forecasting
He et al. (2015)	Model		*	*	Descriptive	Clustering	Fuzzy c-means clustering
Marine-Roig and Clavé (2015)	Model			*	Predictive	Semantic analysis	Text mining, sentiment analysis
Salehan and Kim (2015)	Model		*	*	Predictive	Semantic analysis	Content analysis
Fang and Zhan (2015)	Model		*		Predictive	Semantic analysis	Sentiment mining
Chong et al. (2016)	Model & platform		*	*	Predictive	Semantic analysis	Sentiment mining
Schmidt et al. (2015)	Theory			*	Predictive	Semantic analysis	Sentiment analysis

Table A6: Summary of literature on BDA in "General SCM" papers

Articles	Research type	Level of analytics	BDA model type	BDA techniques
Sheffi (2015)	Theory	Prescriptive	Mixed/others	N/A
Wu et al. (2016)	Model	Descriptive	Clustering	Entropy method, quantitative transformation function
Papadopoulos et al. (2016)	Theory	Descriptive	Semantic analysis	Content analysis, factor analysis
Ong et al. (2014)	Platform	Prescriptive	Mixed/others	Text mining, dashboard visualisation
Zou et al. (2016)	Model	Prescriptive	Mixed/others	Kalman filter algorithm, median filter algorithm
Giannakis and Louis (2016)	Platform	Prescriptive	Mixed/others	N/A